

THESIS

DEVELOP A MULTI-PERIODS FUEL TREATMENTS ALLOCATION MODEL TO FRAGMENT
LANDSCAPE HIGH HAZARD FUEL PATCHES

Submitted by

Warong Suksavate

Department of Forest and Rangeland Stewardship

In partial fulfillment of the requirements

For the Degree of Master of Science

Colorado State University

Fort Collins, Colorado

Summer 2013

Master's Committee:

Advisor: Yu Wei

Chad Hoffman
Robert Kling

ABSTRACT

DEVELOP A MULTI-PERIODS FUEL TREATMENTS ALLOCATION MODEL TO FRAGMENT LANDSCAPE HIGH HAZARD FUEL PATCHES

Increased forest fuel loading and continuity have led to more large fires that can potentially cause the loss of property, life and forest resources in certain forest ecosystems. Strategically fragmenting landscape fuel patches with the potential of carrying high intensity or crown fires helps mitigate the future fire risks. This research develops a mathematic integer programming model to optimally locate fuel treatment locations across a landscape for multiple decades. Solutions are aimed at strategically fragmenting high fire hazard fuel patches that support high intensity fires or crown fires. This model can be used to schedule treatments in each stand by reacting to fire ignition probability, potential fire damages to wildland urban interface (WUI), streams, lakes, and the cost of fuel treatment. A set of prototype test cases based on artificial data are used to demonstrate the model performance and support preliminary analyses. This theoretical model can be extended to study a variety of fuel treatment related management concerns across space and time when realistic data become available.

TABLE OF CONTENTS

ABSTRACT	ii
TABLE OF CONTENTS.....	iii
LIST OF TABLES.....	iv
LIST OF FIGURES.....	v
INTRODUCTION	1
METHOD.....	7
<i>Set and Subscripts</i>	8
<i>Variables</i>	9
<i>Parameters</i>	10
TEST CASES AND ASSUMPTIONS.....	17
TEST RESULTS.....	25
SUMMARY AND DISCUSSION	37
BIBLIOGRAPHY	41
APPENDICES	47

LIST OF TABLES

Table 1. Tested scenarios for fuel treatment layout design.....	20
Table 2. Both the total area of all available fuel breaks and the total area of newly created fuel breaks will vary across time, and are also influenced by the assumed fuel treatment cost.	35
Table 3. Different model parameters influence the objective function value, the minimum weighted value protected from future fires, and the treatment cost over the next three decade.	36
Table 4. The stand's probability of ignition used in Scenarios A, C, D, E; and the rearranged ignition probability used in Scenario B.	47

LIST OF FIGURES

Figure 1. A conceptual frameworks shows the model inputs, data preparation and parameters determination.	14
Figure 2. In this example, all nine stands are assumed to carry high intensity fires under a defined weather condition (a). High intensity fires can spread between adjacent stands and propagate across the entire landscape without treatment (b). If stands six and eight are treated (c), the high fire hazard fuel patch would be fragmented and fire spread path ways would be broken (d) assuming suppression would be effective in both of the treated stands six and eight.	15
Figure 3. A network representation of fuel treatment prescription across 3 decades. Treatment sets “time since the last treatment” of a stand back to one in the following decade, while non-treatment makes this parameter become two in the following decade. Note that we clustered “time since the last treatment” greater or equal than two together in this example.....	16
Figure 4. The location of study area in Larimer County, Colorado, USA.....	21
Figure 5. A landscape map represents: (a) stands boundaries and stand ID; (b) the initial condition of each stand measured by the number of decades since the last treatment. Zero in both (a) and (b) denotes non-forest areas that are not modeled as candidate area for fuel treatments; (c) the existing permanent fuel-break that always carry low intensity fires (black cells) ; (d) the value to be protected from future high intensity fires.....	22
Figure 6. (a) A test case assumes the probability of fire start from any burnable patch calculated through a binomial distribution function given each burnable cell has probability of fire start 0.001 per decade. Stand’s probability of ignition is related to the size of stand. (b) Rearranged	

probability of ignition to create scenario B in table 1. Probability of fire start is not related to stand's size.	23
Figure 7. (a) A test case assumes the cost of treating each cell increases smoothly depended on its distance to the roads. (b) A test case assumes treatment can only be applied in areas less or equal than 0.8 km from the roads.	24
Figure 8. A map represents the fuel-break and treatment allocation in each decade for scenario A1 under the assumption that the cost of treatment is 0.1 per cell.	27
Figure 9. A map represents the fuel-break and treatment allocation in each decade for scenario A1 under the assumption that the cost of treatment is 0.05 per cell.	28
Figure 10. A map represents the fuel-break and treatment allocation in each decade for scenario A1 under the assumption that the cost of treatment is 0.01 per cell.	29
Figure 11. A map represents the fuel-break and treatment allocation in each decade for scenario C under the assumption that the cost of treatment is 0.05 per cell.	30
Figure 12. A map represents the fuel-break and treatment allocation in each decade for scenario A2 under the assumption that the cost of treatment is 0.1 per cell. All forest stands are assumed haven't been treated in the past two decades therefore they would carry high intensity or crown fires at the start.	31
Figure 13. A map represents the fuel-break and treatment allocation in each decade for scenario B in table 1 under the assumption that the cost of treatment is 0.1 per cell with rearranged stand's probability of fire start.	32

Figure 14. A map represents the fuel-break and treatment allocation in each decade for scenario D under the assumption that the cost of treatment linearly increase with distance from road..... 33

Figure 15. A map represents the fuel-break and treatment allocation in each decade for scenario E under the assumption that the cost of treatment is 0.1 per cell and stands beyond 0.8 km from road are unable to be treated..... 34

INTRODUCTION

Due to the exclusion of low-intensity wildfire as the consequence of aggressive suppression since the 20th century, forest fuel accumulation significantly increased the chance of large and high intensity fires in North America (Agee and Skinner, 2005; Cohen, 2008). High intensity crown fires can consume valuable timbers, destroy wildlife habitats, degrade aquatic ecosystem, influence surface water quality, and in extreme cases cause the loss of human lives, properties and public infrastructures (Loehle, 2004). The recent increasing of wildland fire in the United States represent some of the new challenges in forest management (Alig et al. 2004; Spyratos et al. 2007; Schoennagel et al. 2009; Massada et al. 2011; Toman et al. 2011) that requires the policies, and management actions, especially within wildland urban interfaces (WUI), to move to the foreground (Schoennagel et al., 2009; Mell et al., 2010).

The frequent occurrence of wildfire and its devastative behavior are depend on several factors, especially forest fuel in which its characteristic causing the variation of fire ignitions and fire spread (Pyne et al., 1996). Fuel treatment is considered as an important approach to reduce fire intensity and severity by changing fuel characteristics (Martell and Network, 2004; Reinhardt et al., 2008), make wildfire to be controlled more easily (Mell et al., 2010), support safer fire suppression (Kalabokidis and Omi 1998), increase the resistance or zone of friction during fire spread at landscape scale (Gonzalez et al., 2008) and lower wildfire occurrence (Radeloff et al., 2005; Mell et al., 2010). Forest managers often use prescribed burning, thinning or harvesting as methods of fuel treatment (Loehle, 2004). Such fuel treatments represent a process to alter the structure and the quantity of fuel in a forest (Finney, 2001).

Agee and Skinner (2005) pointed out that fuel treatments' primary target is to reduce hazardous fuels by reducing surface fuel loadings, increasing height and decreasing density of crown. Although the effectiveness of treatment, fire propagation and behavior were greatly influenced by spatial distribution of fuel and firebreak networks (Duguy et al., 2007), which usually induce lower chance of crown fire in treated area (Agee and Skinner, 2005; Reinhardt et al., 2008). However, Reinhardt et al. (2008) suggest that fuel treatment shouldn't concentrate in creating fire suppressive conditions to the forest in which will facilitate fire in extreme condition to happen in larger area where wasn't burned. Therefore, fire without destructive consequences is preferred to prevent the continued accumulation of fuel for unmanageable fire events in which is acceptable in the long term of wildfire management. Moreover, fuel treatment might not helping keep forest healthy and restoration of ecosystem (Dombeck et al., 2004; Reinhardt et al., 2008), since fuel treatment often create stands that are different from their historical characteristics and disturb natural processes of fuel accumulation diminishing cycle.

Fuel treatment and fire suppression often work together during wildfire (Reinhardt et al., 2008). If treatments are located in areas accessible to fire fighters during firefighting, they could improve the efficiency of fire suppression. Firefighter can be dispatched more safely to treated areas (Fites et al., 2007; Hudak et al., 2007; Murphy et al., 2007, Pollet and Omi, 2002; Finney and Cohen, 2003; Hirsch et al., 2004; Loehle, 2004; Stratton, 2004) and fuel treatment could improve the visual contact between firefighters, and create safer access and withdrawal paths in and out of the main fire (Moghaddas and Craggs 2008). Factors influencing the efficiency of fuel treatment include treatment prescriptions, time between consecutive

treatments, fire regimes (Region, 2007), forest zoning, fire risk, values at risk, suppression capabilities, and fuel structures (Weatherspoon and Skinner 1996) etc. Although individual treatment might be able to alter fire behavior in local scale, it has limited contribution to change wildfire behaviors at landscape-scale (Kauffman and Martin, 1989; Agee, 1998). The individual treatments can be spatially placed to form network of fuel barriers to influence future fire behaviors. Therefore, treatment topology plays important roles to break the continuity of fuels and affect landscape wildfire behaviors (Finney, 2001; Viedma et al., 2009; Arkle et al., 2012).

To apply fuel treatment in strategic level of planning, selecting and coordinating suitable treatment locations is a complex forest management decision. A large proportion of a landscape may need to be treated to form contiguous fuel breaks if treatments are randomly allocated (Bever et al., 2004). Carefully selected spatial fuel treatment layouts are often more effective in lessening the dangerous of both surface and crown fire, and often result in better efficiency in reducing the rate of fire spread (Finney, 2003, 2008). Loehle (2004) suggested that fuel treatments should be arranged in pattern analogous to bulkheads on a ship under an assumption that treatment reduce the probability of fire ignited to zero. Van Wagtendonk (1995) suggested fuel treatments to be spatially separated to create cumulative effect in changing wildfire size and behavior. Fujioka (1985) and Catchpole et al. (1989) suggested forming treatments into parallel strips perpendicularly to the major fire spread directions to reduce fire spread rates, although this strategy works well only if a future wildfire moves perpendicularly to these strips. Price (2012) suggested that long linear fuel barriers are more effective in reducing the risk from unplanned fire, except gaps within the barrier could lead to

reductions of fuel effectiveness. Some researchers also suggested applying fuels treatments close to highly valuable areas such as WUI (Schoennagel et al., 2009; Massada et al., 2011).

Many models have been developed to support landscape fuel treatment allocation decisions. Mathematical models are necessary in selecting landscape fuel treatment locations, or providing preliminary plans for fire managers. Simulation and optimization models are two major types of decision support models. Simulation models have the advantage of representing detailed ecological function and physical processes during fire spread by accounting for the changes and influences of fuel, topography and weather. Repeated fire simulations help evaluate the effectiveness of various fuel treatments and conditions alternatives. For example, Finney (2006) introduces FlamMap model to evaluate the efficiencies of several regular spatial fuel treatment layouts by simulated fire spread on these different landscapes. Finney (2008) latterly use another simulation method to search for the fastest fire spread path by starting and growing rows of fires. Fuel treatments are then located along these paths to reduce the rates of fire spread. Kim et al. (2009) developed a stand-based model using the great deluge algorithmic to simulate and examine fire spreads under random, aggregated, and regularly distributed fuel treatments.

Optimization model belongs to another category of fuel treatment decision support model. It has the advantage of implementing efficient searching algorithms to systematically evaluate a large number of management options to find the best decision(s) under a set of pre-defined modeling assumptions. Optimization model also supports a rich set of tradeoff analyses that might be difficult to be conducted through simulation approaches (Hof and Bevers, 1998). In fuel treatment allocation problems, the specific objectives of optimization can help seeking

the locations of fuel treatment across the landscapes (Finney, 2006). Hof et al. (2000) developed a spatial linear programming model to schedule fuel treatment to delay the spread of a particular fire to protect preselected locations on an artificial landscape. Bevers et al. (2004) used a graph network model to solve the shortest path problem in an artificial landscape composed by hexagon based cells, and discovered how random scheduling of fuel treatments could form contiguous fuel breaks. Wei et al. (2008) developed two mixed integer programming (MIP) models to locate fuel treatment (1) based on the spatial distribution of fire ignition risks, fire intensities, estimated fire spread probabilities, or (2) by considering the spread of multiple future fires in which the models tend to allocate contiguous fuel treatment depend on the distribution of value to be protected (Wei, 2012). Konoshima et al. (2010) created a spatially explicit dynamic programming model to schedule harvesting and fuels treatments across a hypothetical landscape to study the tradeoffs between timber harvesting and fire loss mitigation and found that despite of homogeneous management units, the spatial configurations can lead to spatially heterogeneous management. Optimization model requires a decision problem to be formed following fixed mathematical structures, therefore often uses generalization assumptions, i.e. linear equations are required by a linear programming model, stages and states are required by a dynamic programming model.

This research focuses on developing of a new MIP model of fuel treatment allocation problem, aimed at breaking fuel patches connectivity at landscape level for multiple periods. In this work, stand is considered as the minimum treatment unit, which is consistent with many other forest management practices (Thompson III et al., 1995). This optimization model relies on strategic level data to conduct fuel patch management by avoiding designing landscape

layouts to target specific fire ignition, fire duration and spread direction. It demonstrates how a MIP model can help schedule fuel treatment layouts across multiple planning periods by account for the change of fuel conditions across time. This represents an improvement from many previous models by considering fuel treatment as a multi-periods decision.

METHOD

In a Mathematical Programming (MP) model, the specific management objective is formed as an objective function, mostly as minimizing losses or maximizing benefits. The objective function value is usually bounded by a set of constraints defining the limitation and boundary of the decision variables (Hillier and Lieberman, 2005), to express the limit and relationship among decision variables. Mixed Integer Programming (MIP) model is a type of MP model, which requires some decision variables to take the integer or binary values. Binary variables can be used to define problems with “yes” or “no” decision (Wolsey, 2000). A MIP model can be written in a general form.

$$\text{Minimize } c'x \quad (1.1)$$

$$\text{Subject to : } Ax \geq b. \quad (1.2)$$

$$lb \leq x \leq ub \quad (1.3)$$

Variables x are decision variables and the c vector contains the coefficients of decision variables. c and x form the objective function (1.1). The objective function is subject to a set of constraints (1.2). A is a (m by n) matrix representing coefficients of decision variables in the constraint. m is numbers of constraints, and n is numbers of decision variables. b is vector containing the right hand side of all constraints. Function set (1.3) defines the lower and upper bounds of every decision variable. For Boolean type decision variables, their values are either 0 or 1. In this research, spatial and temporal components were added to the optimization model by populating the objective function and constraints with parameters and variables indexed i

and j which denote spatial configuration and period order respectively. That means each variable and constant will occur for each spatial and temporal unit.

To help define the parameters for the constraints, a diagram (figure 1) shows the input data for this model. Weights and values, such as fire ignition probability, fuel treatment costs and value to be protected from fires in each location, are required to be determined as model parameters in cons. We acknowledge the complexity and uncertainties in collecting and preparing the input data required by real world fuel treatment layout planning, especially across multiple periods. Although data preparations, parameterization and post analyses are critical in real world fuel treatment planning, they were not the emphasis of this study. So, at the purely conceptual level, we define the variables and parameters as follows.

Set and Subscripts

P and p : the set and index of periods in the model.

C and c : the set and index of cells in a landscape.

A and a : the set and index of management units (stands) in a landscape.

C_a : the set of cells within stand a .

C_c : the set of neighboring cells of cell c (sharing edge or corner).

J, J' and j, j' : the set and index of “time since the last treatment”.

K, K' and k, k' : the set and index of option for fuel treatment prescriptions. $k=0$ denotes “no treatment”; $k=1$ denotes treatment.

Variables

$m_{p,a,j,k}$: binary variable tracking whether fuel treatment will be implemented in period p in management unit (stand) a with the time since last treatment for stand a being j . $k=0$ for no treatment, $k=1$ for treatment.

$t_{p,a,c}$: continuous variable between zero and one. It tracks whether high intensity fire (or crown fire) could spread from stand a to cell c without encountering any fuel breaks. The value of this variable would be naturally set to either zero or one by the model without being defined as a binary variable. $t_{p,a,c} = 0$ denotes that high intensity fire will spread into cell c without encountering fuel breaks; $t_{p,a,c} = 1$ otherwise.

tc : continuous variable, a linear function of the choices $m_{p,a,j,k}$, representing the total cost of fuel treatment in all modeled periods in the landscape.

f_{min} : continuous variable. Because we are planning the treatment locations for multiple periods, the value protected from high intensity fires may vary between different planning periods. This variable is a function of the choices $m_{p,a,j,k}$ and is used to track the minimum value protected across all periods. A Max(Min) type of formulation (Hof et al. 1986) can be used later in the model to avoid high potential fire loss in any of the planning periods.

Parameters

L_c : value to be protected from fire in each cell r (loss if burned)

$E_{j,k}$: a parameter set to 1 if fire is assumed to be controlled in stand j based on the “time since the last treatment” of j , and the treatment option selected for j ; 0 if fire is assumed to spread across a stand.

$I_{p,a}$: the probability of a fire ignited from stand a within the next discrete planning period. In this research, the periodic interval is set to be one decade.

$V_{p,a,j,k} : V_{p,a,j,k=1} > 0$ denotes that the positive discounted cost of treating stand a when the time since the last treatment for this stand is j . In the other hand, $V_{p,a,j,k=0} = 0$ denotes that there is no treatment cost if stand a is not treated.

With the variables so defined, the optimization problem is to choose $m_{p,a,j,k}$ to minimize

$$Z = tc - f_{min} \quad (2.1)$$

Subject to:

$$t_{p,a,c} \leq \sum_j \sum_k m_{p,a,j,k} \times E_{j,k} \quad \forall p \in P, a \in A, c \in C_a \quad (2.2)$$

$$t_{p,a,c} \leq t_{p,a,c'} + \sum_j \sum_k m_{p,\hat{a}=A_c,j,k} \times E_{j,k} + \sum_j \sum_k m_{p,\check{a}=A_{c'},j,k} \times E_{j,k} \quad \forall p \in P, c \in C, c' \in C_c \quad (2.3)$$

$$f_{min} \leq \sum_a \sum_c t_{p,a,c} \times L_c \times I_{p,a} \quad \forall p \in P \quad (2.4)$$

$$\sum_k m_{p=1,a,j=j_1,k} = 1 \quad \forall a \in A \quad (2.5)$$

$$\sum_k m_{p=1,a,j \neq j_1,k} = 0 \quad \forall a \in A \quad (2.6)$$

$$\sum_{j'} \sum_{k \in K_{j'}} m_{(p-1),a,j',k} - \sum_k m_{p,a,j,k} = 0 \quad \forall a \in A, j \in J, p \in \{2 \text{ to } P\} \quad (2.7)$$

$$\sum_p \sum_a \sum_j \sum_k V_{p,a,j,k} \times m_{p,a,j,k} = tc \quad (2.8)$$

$$\sum_a \sum_j \sum_k A_a \times m_{p,a,j,k=1} \geq R \times \sum_a \sum_j \sum_k A_a \times m_{p-1,a,j,k=1} \quad \forall p \in \{2 \text{ to } P\} \quad (2.9)$$

$m_{p,a,j,k}$ are binary variables, $t_{p,a,c} \in [0,1]$

This model tracks the total value protected in a landscape from crown fires in a planning period. The bookkeeping variable f_{min} defined by constraints (2.4) is used to track the minimum value protected among all planning periods. In the current model design, the objective function (2.1) minimizes the sum of $(-f_{min})$ and the cost of placing fuel treatment in all periods. Minimizing $(-f_{min})$ is equivalent to maximizing f_{min} . Alternative model designs can also be adopted without significant changes of the current mathematical formulation. For example, new constraints can be added to limit the total treatment cost or restrict the fire damages.

Fuel condition would also be altered across periods based on the time since the most recent treatment of each stand. This basically assumes a direct connection between crown fire potential in a stand and the duration since the last treatment of this stand. Stands with crown fire potential may be connected and form contiguous high fire hazard fuel patches. In case a fire ignited in such a fuel patch, suppression may not be able to stop it until natural or manmade fuel breaks are encountered. The connectivity of crown fire potential fuel patches are identified through stands connection constraints (2.2) and (2.3). Crown fire potential patches formed by connected stands (figure 2a and 2b) can be fragmented if fuel treatments are scheduled in certain stands to lower the potential and provide suppression opportunities

(figure 2c and 2d). Constraints (2.2) defines that after a fire ignited in stand a in period p , values associated with the cells in this stand will be lost if this stand itself can carry crown fires.

However, if a stand has been treated recently, a fire started from this stand will be assumed as controllable; therefore the values within this stand can be protected from this fire. Constraint set (2.3) tracks whether fire originated from stand a could spread to any other locations (raster cells) in the landscape. This constraint reflects a built-in rule of the model that any fire started from a stand can and only can spread into areas within the same high fire hazard patch.

Treatments are scheduled by the model to fragment these higher fire hazard patches to prevent fire spread.

Constraints set (2.5) restricts that one and only one treatment prescription can be applied to stand a during each planning period. In case that both prescribed burning and mechanical thinning are applied in a stand in a period, a new prescription type may be created to reflect the combined treatment. Constraints set (2.9) define the transition of stand fuel conditions, reflected by the time since the last treatment in this stand, across time. The connection between decision variables across time is illustrated in figure 3. Constraint (2.10) sums the discounted cost from all treatments scheduled in multiple planning periods. The total discounted cost is a component of the objective function. Constraint set (2.11) is optional. If included, it enforces certain level of even-workload for fuel treatment. It requires that the treated area at period p must be greater or equal to a proportional of the treated area in the previous period. This proportion is defined by parameter R , which can be set to any positive number. Setting R as 0 means there is no restriction for the changing of treatment workload

between two consecutive periods; setting R to be greater or equal than one mean that the treated area in any period must be at least equal to the treated areas in its previous period.

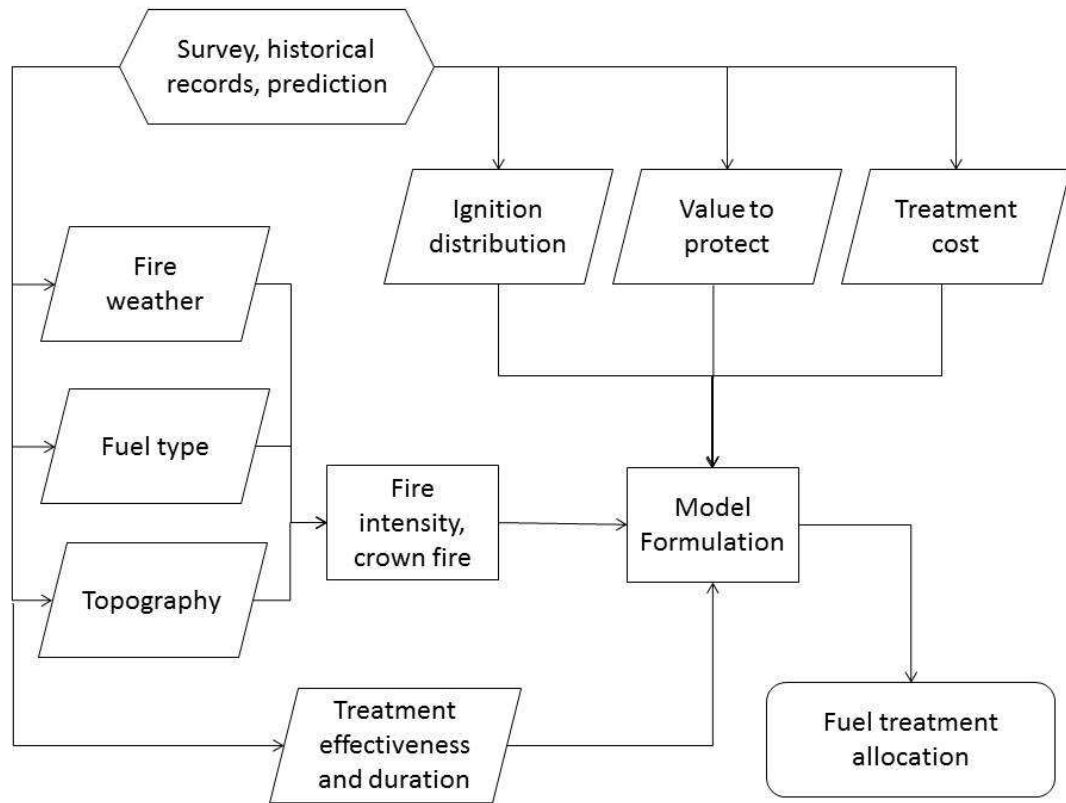


Figure 1. A conceptual frameworks shows the model inputs, data preparation and parameters determination.

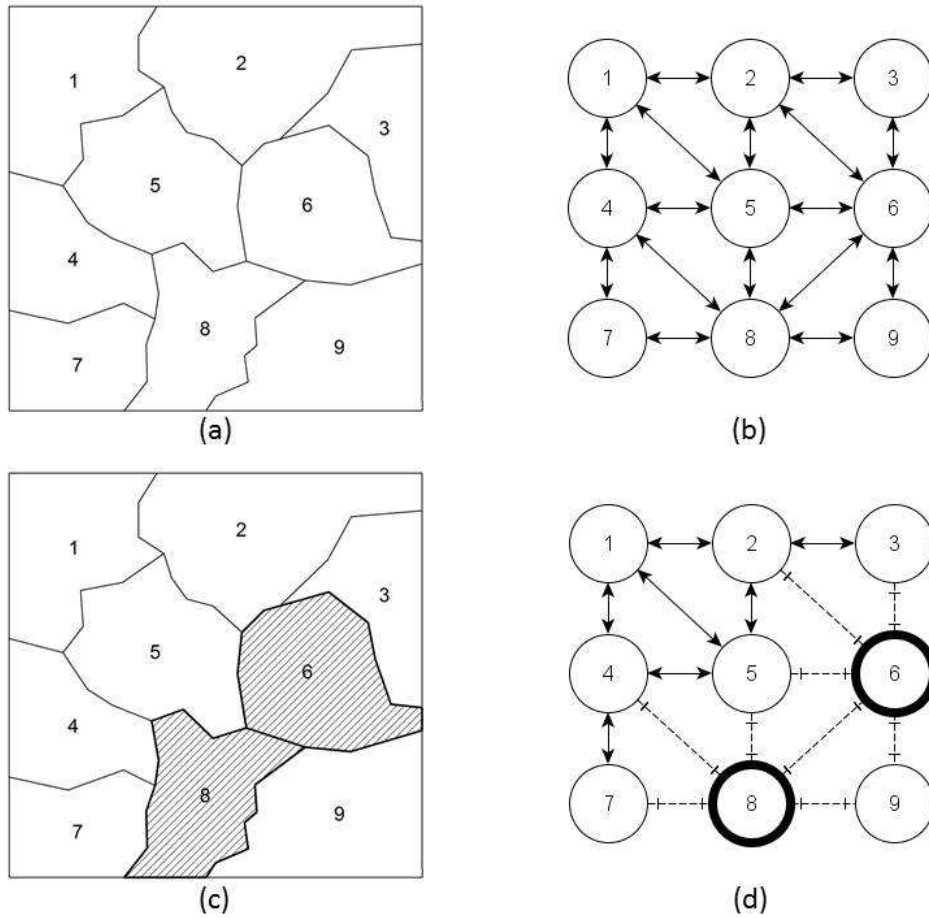


Figure 2. In this example, all nine stands are assumed to carry high intensity fires under a defined weather condition (a). High intensity fires can spread between adjacent stands and propagate across the entire landscape without treatment (b). If stands six and eight are treated (c), the high fire hazard fuel patch would be fragmented and fire spread path ways would be broken (d) assuming suppression would be effective in both of the treated stands six and eight.

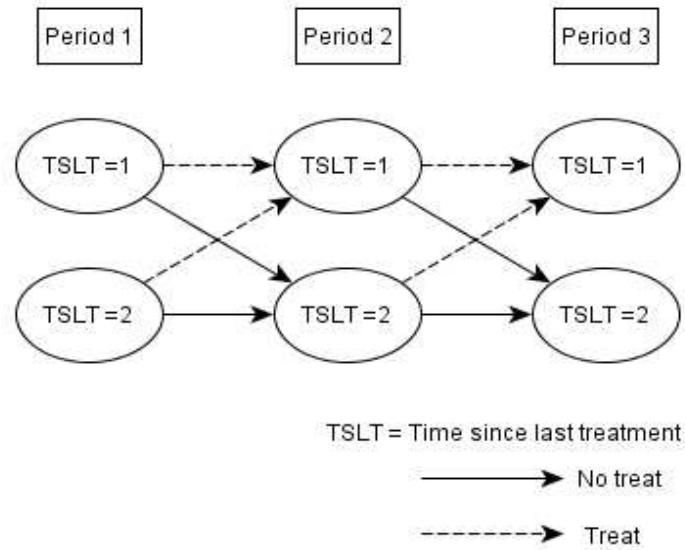


Figure 3. A network representation of fuel treatment prescription across 3 decades. Treatment sets “time since the last treatment” of a stand back to one in the following decade, while non-treatment makes this parameter become two in the following decade. Note that we clustered “time since the last treatment” greater or equal than two together in this example.

TEST CASES AND ASSUMPTIONS

We conducted a set of tests by applying this model on a landscape in the vicinity of Roosevelt National Forest, Comanche Peak Wilderness Area, and the Larimer County of Colorado (figure 4). The tested landscape was delineated into thirty stands (figure 5a) by using orthographic images, land cover data, elevation, and the land ownership map. Stands' size in this test case varies between 1 to 72 hectares. We excluded urban, grassland, bare land, shrub land, and lake from fuel treatment. Raster layers are used to track details such as treatment cost and value to be protected from fires. Each stand includes multiple raster cells with each cell is a 150 by 150 meters square. Note that although certain attributes of this tested site were described using real data to reflect certain fire management realities (i.e. existence of forest, WUI, roads and streams), the other key attribute layers were made up. Some variations of input data layers are arbitrarily created later to support sensitivity analysis. These artificial data layers include fire ignition probability, the values to be protected from fire, the initial condition of the forest measured by the time since the last treatment, and the cost of treatment in each cell. This model designs fuel treatment layout within each of the three consecutive decades for different testing scenarios with the objective of breaking potential crown fire fuel patches. ESRI ArcGIS 10 was used to prepare the model inputs. Visual Basic and IBM Ilog CPLEX are used to populate and solve the MIP model.

We constructed six testing scenarios (*table 1*) to reflect a range of possible decision contexts in fuel treatment. These six scenarios share a list of common assumptions:

1. Values to be protected from fire. Cells within 150 meters buffer of any urban parcels are on our priority list to be protected from high intensity or crown fires. These cells are assigned a value of one per cell. Cells within 150m buffer of lakes and streams were assigned a lower value to be protected as 0.5. Other burnable cells in the landscape are assigned a value to be protected of 0.2. The total value to be protected in each cell will be summed across multiple attribute values (figure 5d).
2. Treatment is assumed to be scheduled in the middle of each decade. We use a four percent annual rate to discount fuel treatment cost in each of the planning decades.
3. We classify the fire into two categories. Surface fire is assumed in non-forested areas (figure 5c), or recently treated forested areas. Crown fire is assumed to be possible under a generally targeted weather condition (not specified in this study) in stands that have not been recently (one or two decades depending on specific test scenarios) treated. We recognize that identifying areas with high intensity or crown fire potential is a complex process as it relies on weather conditions, topography and past fuel treatment types. However, since this is not the emphasis of this research, we simply use the time since the last treatment as the only factor considered.
4. We assume cells not supporting crown fires would serve as effective fuel-breaks to support aggressive suppression and stop fire spread. This represents an optimistic management scenario.
5. Area outside of the studied landscape is considered unburnable.

Besides the common assumptions, each of the six tested scenarios also adopts some unique assumptions, mostly for sensitivity testing to study model behaviors.

1. We created and tested two cases of artificial fire ignition probability distributions. In the first case, we assume that the probability of a fire to start from any burnable cell in each decade is a constant of 0.001. Therefore, the probability of a fire starting from each stand can be calculated through a binomial distribution function (Attachment 1). A larger stand will be assigned a higher fire ignition probability. In the second test case (only applied to the testing scenario *B* in table 1), we rearranged each stand's fire ignition probability (figure 6) for sensitivity analysis.
2. We tested two possible longevities of fuel treatment effects in preventing crown fires: one, or two decades. Most of the scenarios assume fuel treatment effects would last for two decades. Scenario C assumes the fuel treatment effectiveness would only last for one decade.
3. We assume that "time since last treatment" could affect the cost of the next treatment in most of the scenarios. Therefore, the per-acre cost of treating a stand that has been treated within the last decade is only half the per-acre cost of treating the same stand if it has not been treated recently. The only exception is scenario C (table 1), in which the per-acre cost of treating each stand would not change according to the time since the last treatment.
4. We tested three spatial fuel treatment cost distribution scenarios: i) homogeneous treatment cost across the landscape; ii) the cost of treating a cell increases as it is

farther away from a road (figure 7a); iii) the cost of treating a cell > 0.8 km from any road is too high to be viable (Figure 7b).

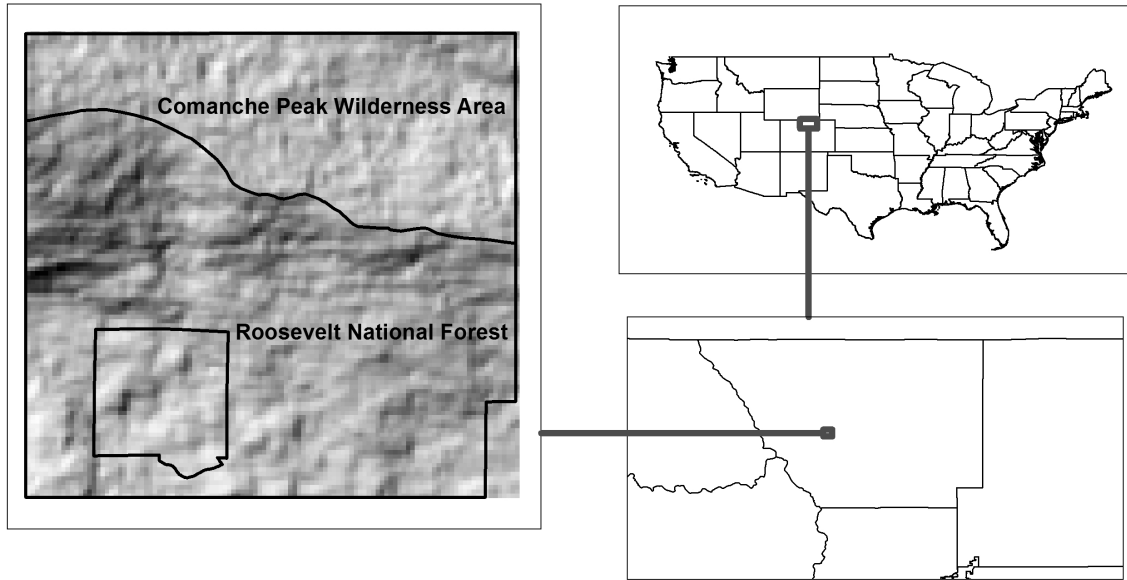
5. We also tested a case where all stands are assumed to be currently in a condition that fuel treatment is required to prevent high intensity or crown fire within them (Scenario A2 in table 1).

Table 1. Tested scenarios for fuel treatment layout design

Scenario ID	Fire ignition probability from each cell (per decade)	Fuel treatment cost (arbitrary unit)	Duration of fuel treatment effectiveness (decade)
A1	0.001	Homogeneous	2
A2*	0.001	Homogeneous	2
B	Rearranged randomly	Homogeneous	2
C	0.001	Homogeneous	1
D	0.001	Increase by the distance from the road	2
E	0.001	Homogeneous; > 0.8 km from the road is unviable	2

*changing the initial stand condition by assuming all stands can carry high intensity or crown fires initially at the start of the planning horizon

Locational Map of study site



Study site located in Larimer County, Colorado USA.
The site has total 2,224 acres of Arapahoe National Forest and Commanche Peak Wilderness Area.

Figure 4. The location of study area in Larimer County, Colorado, USA.

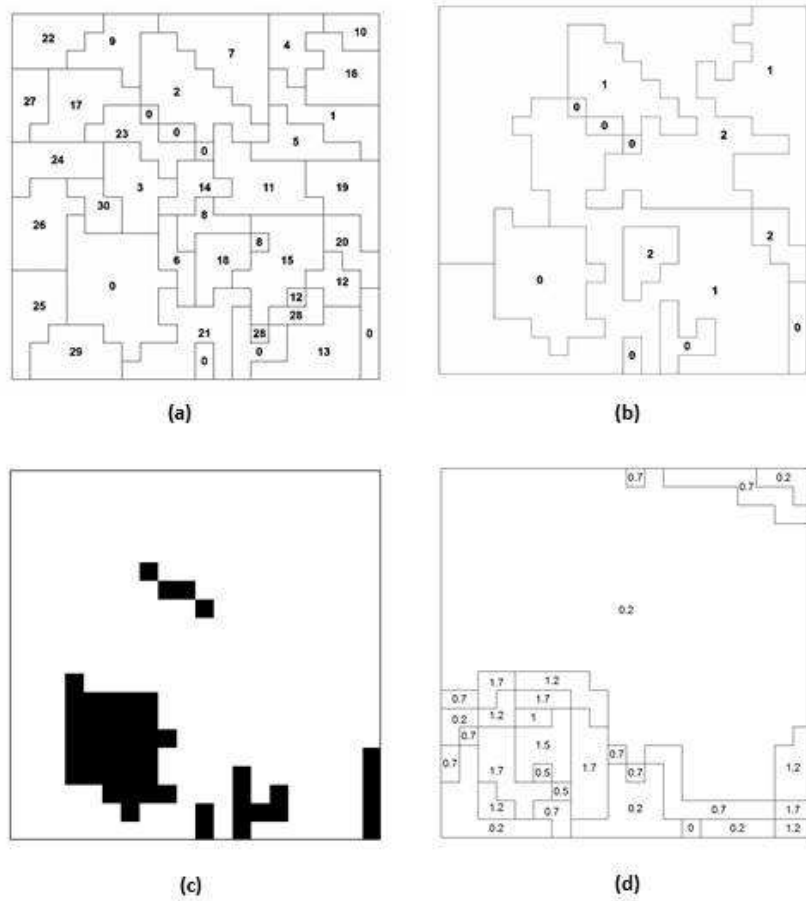


Figure 5. A landscape map represents: (a) stands boundaries and stand ID; (b) the initial condition of each stand measured by the number of decades since the last treatment. Zero in both (a) and (b) denotes non-forest areas that are not modeled as candidate area for fuel treatments; (c) the existing permanent fuel-break that always carry low intensity fires (black cells) ; (d) the value to be protected from future high intensity fires.

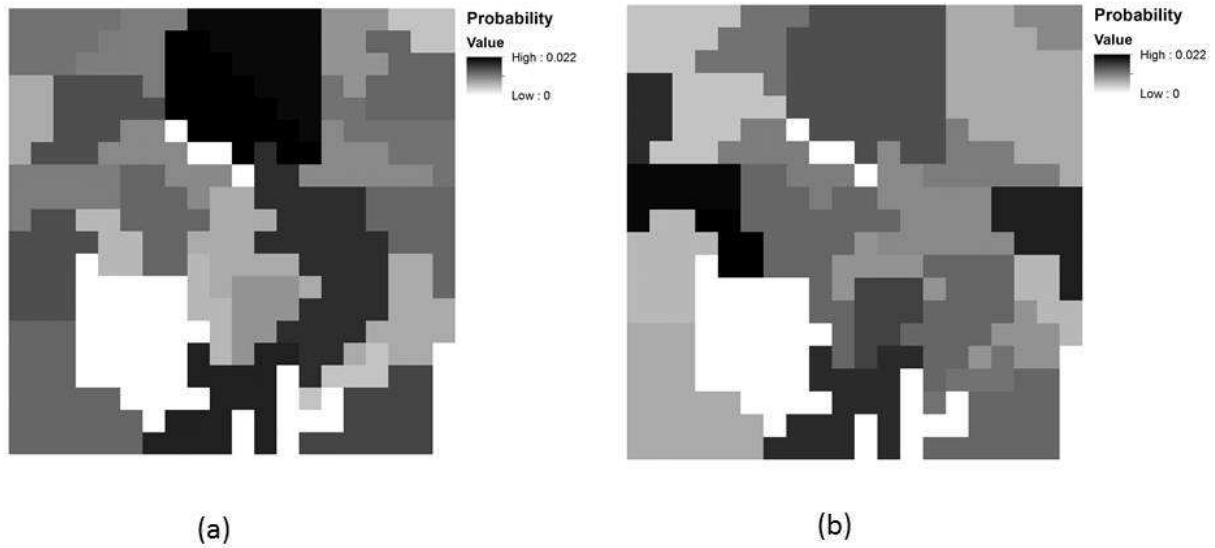


Figure 6. (a) A test case assumes the probability of fire start from any burnable patch calculated through a binomial distribution function given each burnable cell has probability of fire start 0.001 per decade. Stand's probability of ignition is related to the size of stand. (b) Rearranged probability of ignition to create scenario B in table 1. Probability of fire start is not related to stand's size.

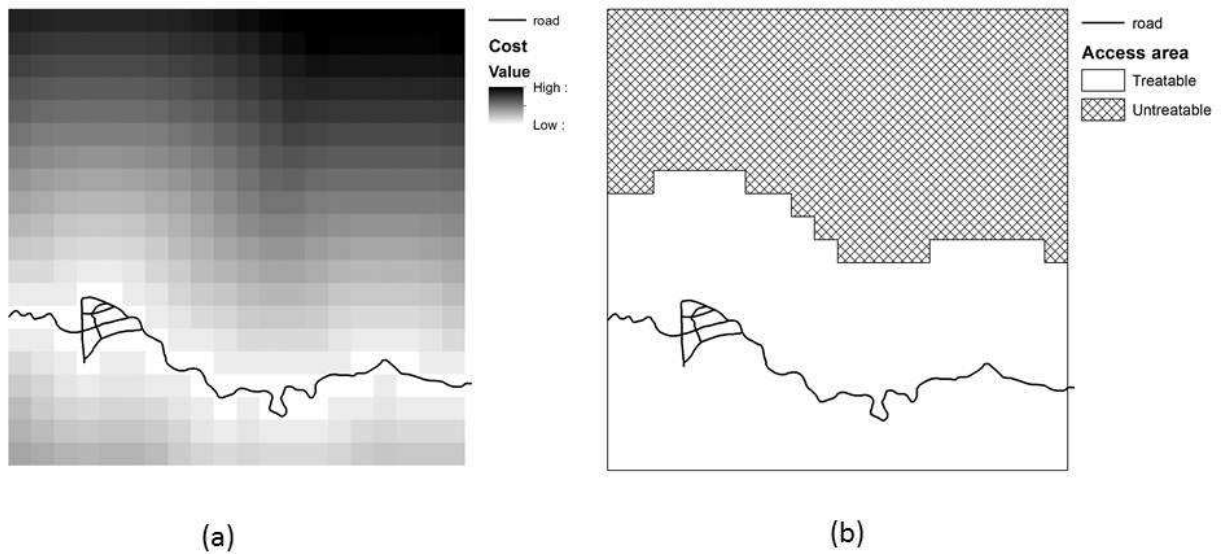


Figure 7. (a) A test case assumes the cost of treating each cell increases smoothly depended on its distance to the roads. (b) A test case assumes treatment can only be applied in areas less or equal than 0.8 km from the roads.

TEST RESULTS

This model suggests building fuel breaks across multiple periods by connecting sets of adjacent stands to fragment high fire hazard fuel patches composed by stands that have not been treated for more than one or two decades depending on the tested assumptions. We are interested in building landscape structures in which high fire hazard fuel patches are fragmented. Besides the existing natural fuel breaks such as lakes in a landscape, areas that can serve as fuel breaks are also composed by either the newly treated area in each decade, or by the areas treated from the earlier decade while these areas are still deemed as effective in dropping fire intensities. Increasing the per cell based fuel treatment cost caused this model to select less number of cells to treat in each period, and also to maintain a smaller area of overall fuel breaks across time (table 2). While the per cell based fuel treatment cost increase, the model would suggest us to accept a higher level of future fire losses (table 3) without surprise.

The overall landscape layouts of fuel breaks is determined by three components: 1) cells newly treated in the current decade, 2) cells treated in a previous decade and still being effective in decreasing fire intensity, and 3) cells of natural fuel breaks. Changing the per cell based treatment costs influence both the spatial layouts of new treatments in each decade, and the overall fuel breaks maintained across time (figure 8, 9 and 10). When the per cell based fuel treatment cost is set to 0.1, this model suggested only scheduling treatment during the second decade (figure 8b) to lower the treatment cost. Decreasing per-cell based treatment cost from 0.1 to 0.05 or 0.01 would add new treatments to decade one (figure 9d), or decade three (figure 10f). With lower treatment cost, more cells are also treated in the second decade (figure 9e and figure 10e).

If we assume that the effects of fuel treatment in preventing crown fire or high intensity fires can last for two decades as suggested in most of the tested scenarios (except scenario C), this model would recognize that it is unnecessary to treat a cell repeatedly in all three decades. For example, a treated cell (or stand) at decade two can be used to fragment the high fire hazard fuel patches in both the second and the third decades. Although cells assigned for new treatment in each decade may vary, the overall fuel-break layouts are often consistent across the three planning decades (figure 8a to 8c, 9a to 9c, and 10a to 10c). However, if the fuel treatment effect of decreasing fire intensity is assumed to only last for one decade before a repeated treatment is necessary (Scenario C in Table 1), this model would tend to treat the same sets of stands repeatedly in different decades to maintain the same layout of the effective fuel breaks (Scenario D in Table 1). An additional test scenario D also suggested that the overall fuel treatment layout could be created and maintained from various initial forest conditions (e.g. comparing figure 8 and figure 12).

Many other factors may also have substantial influence to the model selected spatial treatment layouts across time. For example, Scenario B shows the changing of fuel treatment patterns due to the influence of spatial distribution of fire ignition probability from each stand (figure 13, Scenario B in Table 1). Scenario D tests a case that the cost of fuel treatment in each cell increases from 0 to 2 (mean is 0.745) as it is scheduled farther from a road. Scenario E assumes stands 0.8 km (about half mile, this is an arbitrarily selected number) away from any road would not be treated. Test result shows that treatments are re-schedule between some stands to reflect the changing of treatment costs (figure 14 and 15).

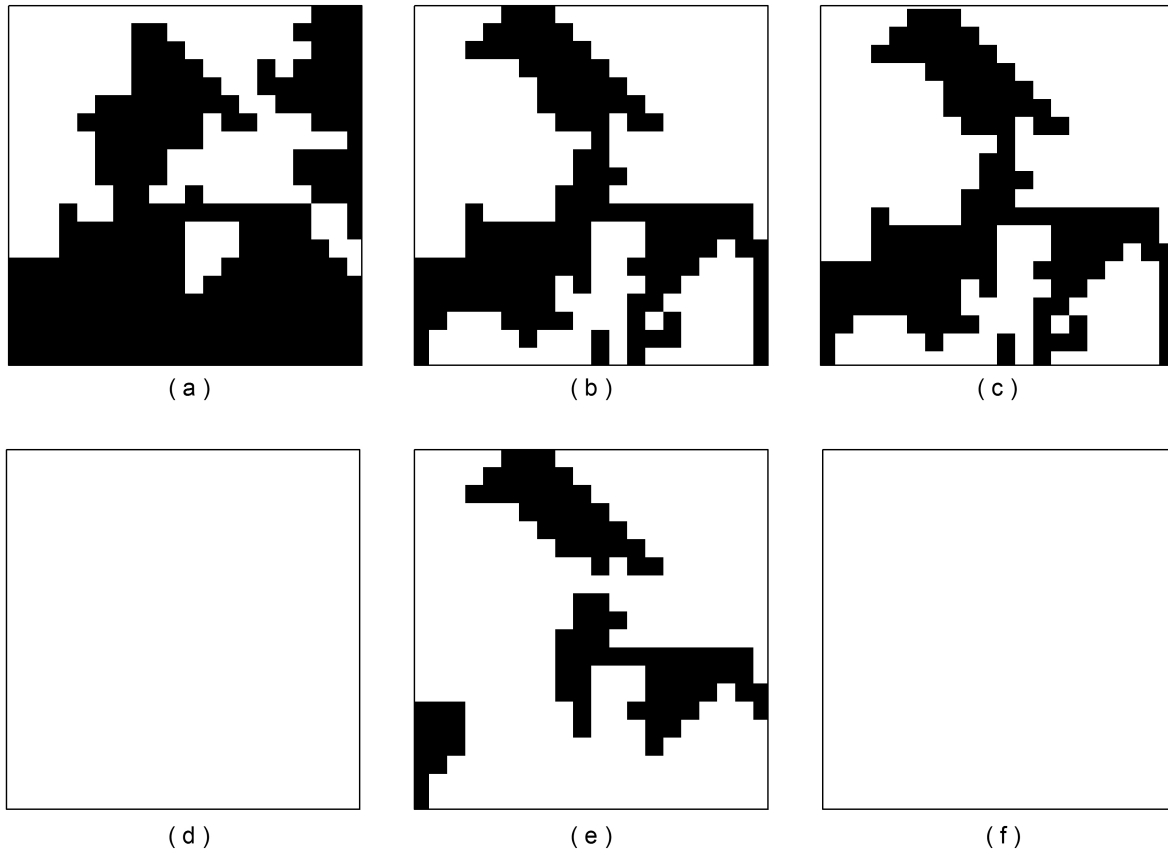


Figure 8. A map represents the fuel-break and treatment allocation in each decade for scenario A1 under the assumption that the cost of treatment is 0.1 per cell.

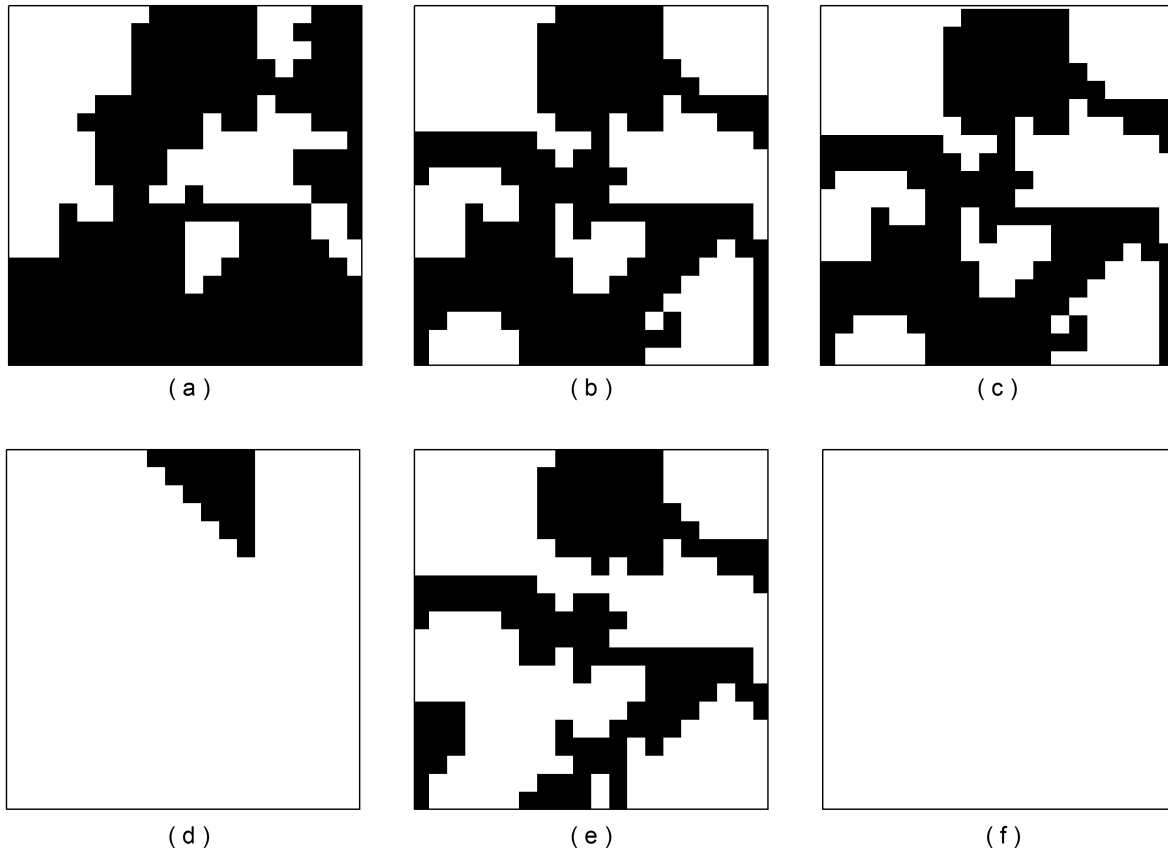


Figure 9. A map represents the fuel-break and treatment allocation in each decade for scenario A1 under the assumption that the cost of treatment is 0.05 per cell.

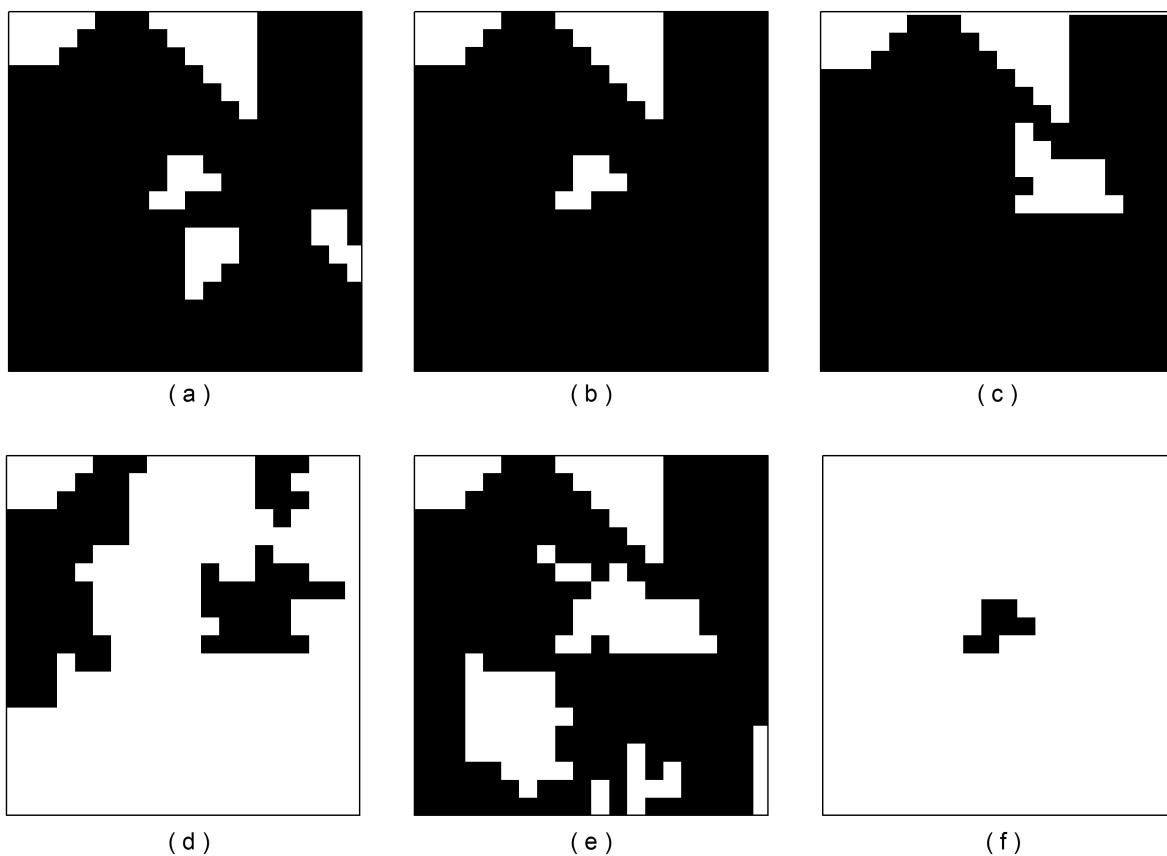


Figure 10. A map represents the fuel-break and treatment allocation in each decade for scenario A1 under the assumption that the cost of treatment is 0.01 per cell.

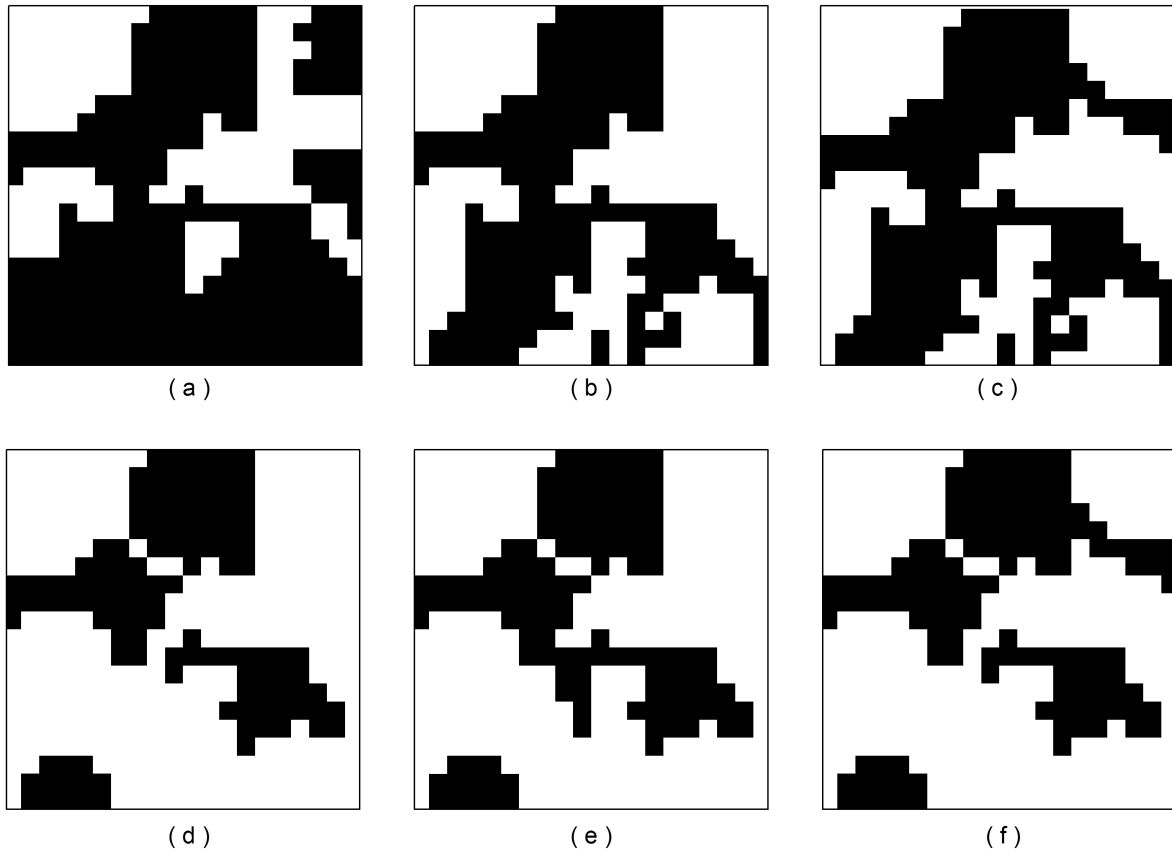


Figure 11. A map represents the fuel-break and treatment allocation in each decade for scenario C under the assumption that the cost of treatment is 0.05 per cell.

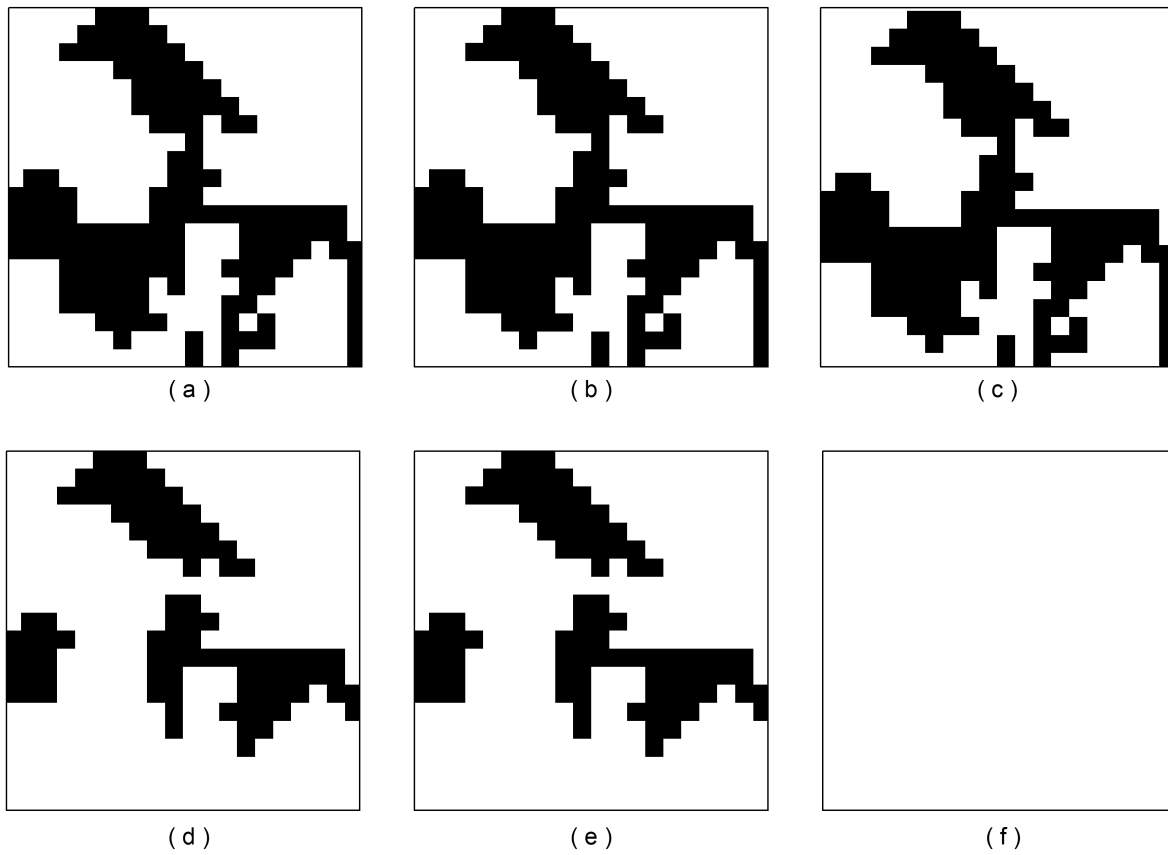


Figure 12. A map represents the fuel-break and treatment allocation in each decade for scenario A2 under the assumption that the cost of treatment is 0.1 per cell. All forest stands are assumed haven't been treated in the past two decades therefore they would carry high intensity or crown fires at the start.

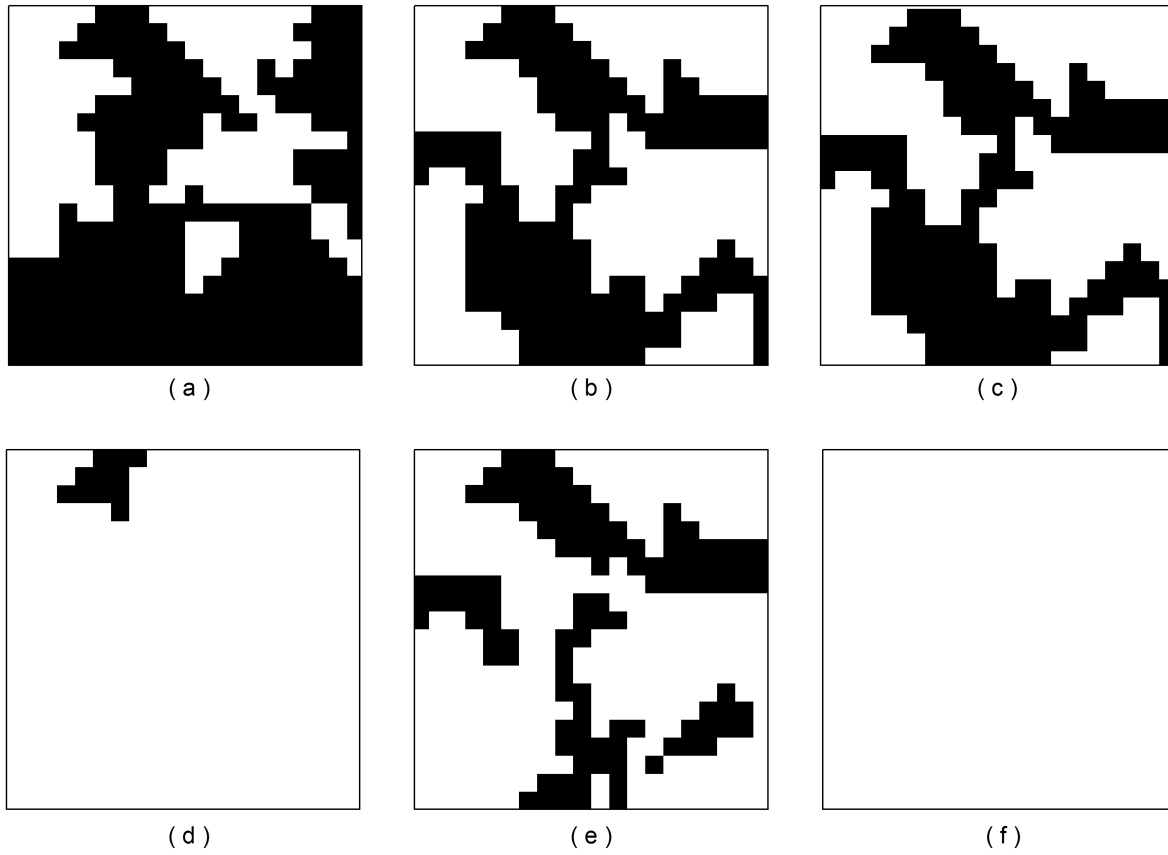


Figure 13. A map represents the fuel-break and treatment allocation in each decade for scenario B in table 1 under the assumption that the cost of treatment is 0.1 per cell with rearranged stand's probability of fire start.

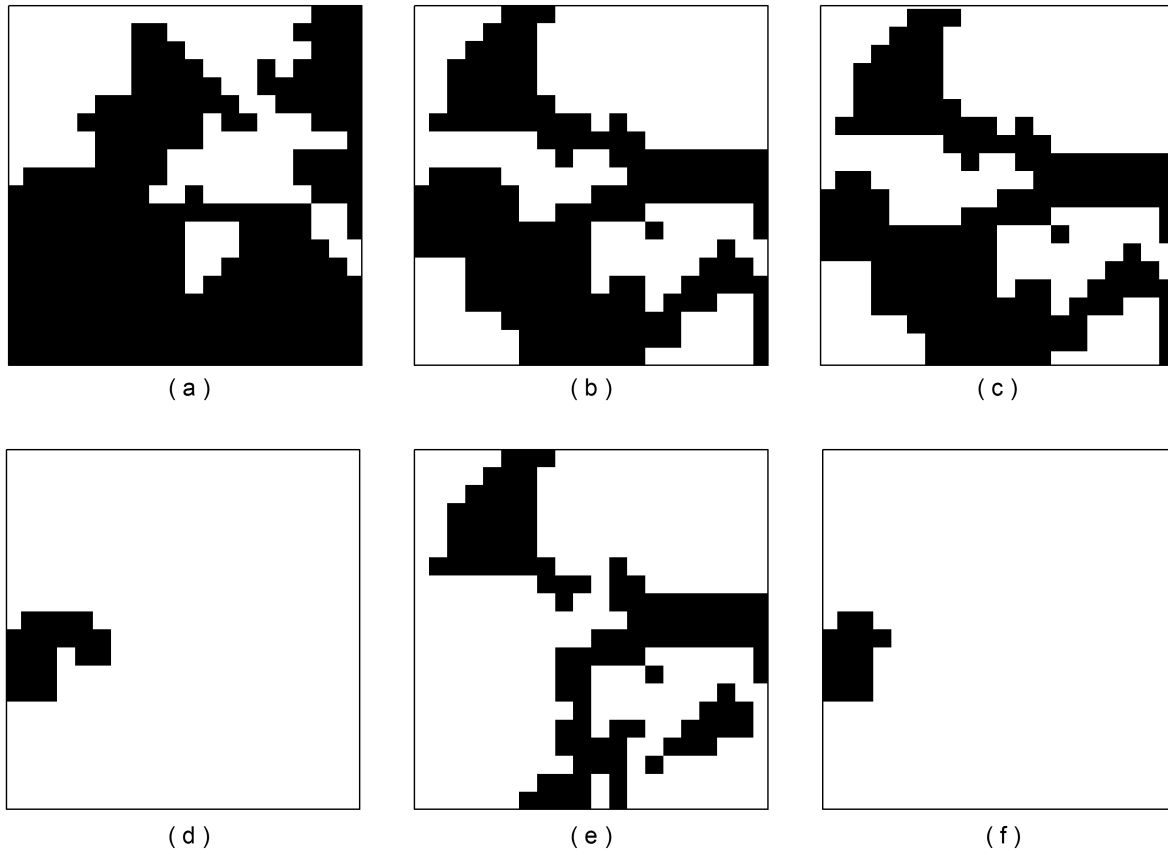


Figure 14. A map represents the fuel-break and treatment allocation in each decade for scenario D under the assumption that the cost of treatment linearly increase with distance from road.

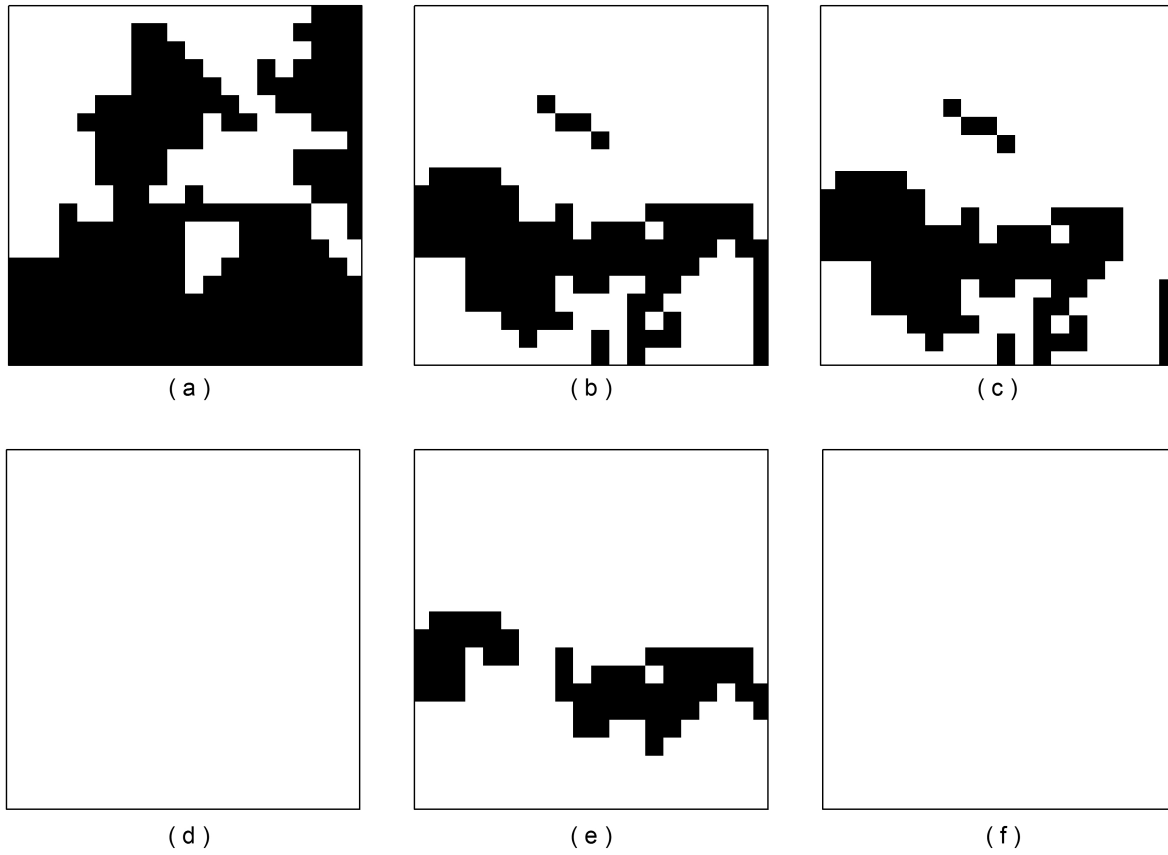


Figure 15. A map represents the fuel-break and treatment allocation in each decade for scenario E under the assumption that the cost of treatment is 0.1 per cell and stands beyond 0.8 km from road are unable to be treated.

Table 2. Both the total area of all available fuel breaks and the total area of newly created fuel breaks will vary across time, and are also influenced by the assumed fuel treatment cost.

Scenario	Cost	Number of cells serving as fuel breaks			Number of cells treated		
	per cell	period 1	period 2	period 3	period 1	period 2	period 3
A1	0.10	242	141	141	0	91	0
A1	0.05	263	200	200	21	150	0
A1	0.01	344	360	349	102	292	7
A2	0.10	143	143	143	93	93	0
B	0.10	253	166	166	11	116	0
B	0.01	303	306	299	61	249	0
C	0.05	262	178	190	122	128	134
D	[0, 0.20]	263	182	176	21	111	15
E	100 or 0.10	242	111	104	0	61	0
E	100 or 0.01	242	172	159	0	122	0

Table 3. Different model parameters influence the objective function value, the minimum weighted value protected from future fires, and the treatment cost over the next three decade.

Scenario	Cost	Objective	F_{\min}	Total
	per cell	value		treatment cost
A1	0.10	-28.193	34.343	6.150
	0.05	-32.701	38.471	5.770
	0.01	-37.663	40.413	2.750
A2	0.10	-22.107	34.557	12.450
B	0.10	-29.004	37.570	8.566
	0.01	-38.157	40.268	2.111
C	0.05	-28.352	36.499	8.147
D	0 to 0.20	-30.963	36.692	5.729
E	0.10	-23.892	28.012	4.120
	0.01	-28.878	29.702	0.824

SUMMARY AND DISCUSSION

Allocating fuel treatments across space and time is an important component of wildland fire management decisions. This research develops a mixed integer programming model to allocate fuel treatments across a spatially gridded landscape across multiple planning periods. Stand is considered as the smallest treatment unit to match the common forest management practices. The test cases provided preliminary results and demonstration of using this modeling methodology to allocate fuel treatments across space and time.

Because of the uncertainty in future fire ignition locations, fire weathers (wind, moisture etc.), fuel accumulation speed, and fire suppression conditions, finding a spatial fuel treatment layout to perfectly fit to all future fire scenarios may be difficult, if it is not impossible. As some research pointed, fuel continuity is an important factor influencing fire risk (Arkle et al., 2012; Ireland et al., 2012). Instead of predicting and integrating all details of future fire conditions into strategic fuel treatment layout design, which would be a daunting task, this model follows an intuitive approach to schedule fuel treatments to break fuel contiguity and fragment high fire hazard fuel patches. We assume, when encountered effective fuel breaks, the intensity of a fire would likely decrease to a level that fire suppression would be successful.

Assumptions adopted by this model simplified the complex biological and economic processes determining the fuel treatment effectiveness and treatment cost. We assume that fuel condition and treatment cost in a stand is a function of the time since the last treatment in the stand. In this study, we assumed this type of information is known and homogeneous across the tested landscape. In reality, the effectiveness of treatment in lowering fire intensity may depend on other factors such as pretreatment conditions, method used for treatment, and

the fuel accumulation speed on treatment sites (Reinhardt et al., 2008). Stand specific treatment cost may vary depending on the topographic nature of the sites and the time since the last treatment etc. Parameterizing this model to reflect the variation of fuel conditions and treatment cost between stands requires detailed field surveys and long term monitoring. It may be possible to design unique fuel succession pathways and treatment cost function for every stand based on their attributes and location when detailed survey and monitoring data are available. These researches are beyond the scope of this study, but would be important in implementing this type of approaches in real world fuel treatment planning.

Certain areas in a landscape are assumed to have higher priority for fire to be absence, for example residential area, recreational area, fragile habitat, old forest stands, or habitat of endangered species etc. According to Schoennagel et al. (2009), fuel-breaks should be placed in areas near or around places with high value to be protected. This model used a set of simple rules to assign values of protection to each cell based on its attributes and locations. Results suggest maintaining consistent spatial patterns of fuel breaks while allowing changes of new fuel treatment locations during different planning periods. It demonstrated that spatial fuel treatment does not have to be scheduled only in areas with higher value of protection. Fuel treatment can also be used to isolate the higher valued areas from fires starting from the other parts of the landscape assuming suppression can be success in treated area. This assumption apparently represents an optimistic planning scenario because suppression may not be successful even in recently treated areas. There are multiple ways to soften this optimistic assumption. For example, additional constraints can be set to reflect the possibility that there are only limited suppression resources to cover certain percentage of the treated areas (Wei

2012). We can also filter out the stands that are difficult to reach or conduct suppression from treatment before scheduling fuel treatments in the remaining stands. Other alternatives may be building a stochastic programming model to explicitly model many possible fire and suppression scenarios. However, this may be a very challenging task due to the complexity of predicting the future fire and suppression conditions.

Some basic sensitivity analyses have been conducted in this study regarding treatment cost, duration of treatment effectiveness and initial forest conditions. It shows that the density and distribution of fuel treatment across the landscape are affected by the combination of both characteristics of spatial units and its locations in the landscape. Although, parameters of objective function, weights for treatment cost and value to be protected, can enlarge or reduce the magnitude of these effects by changing value, it cannot change the spatial distribution of the results unless the spatial distributions of spatial units' features are altered. However, extended future studies would be necessary to more thoroughly understand how the model parameters and assumptions could influence the fuel treatment landscape design. For example, $m_{p,a,j,k}$ can be defined to incorporate specific treatment methods into the model: $k \in \{\text{prescribed burning, mechanical treatment, and mastication etc.}\}$; $E_{j,k}$ set to reflect the effective duration of each treatment type k . Removing ladder fuels in a stand through mastication could potentially having longer treatment effectiveness than prescribed burning. However, there may be an area limitation of how many acres of mastication could be allowed in treatment a landscape. This type of restrictions can be reflected by additional constraints.

$$\sum_a \sum_j m_{p,a,j,k=mastication} \leq A_p \quad \forall p$$

For another example, $V_{p,a,j,k}$ in the model is set to reflect the cost of implementing different treatment types in a stand. In case that fuel treatment can be combined with commercial timber operations, the benefit of timber return from each treatment type k can be accounted in the objective function to support tradeoff analysis. Further study on built-in rules, parameters, variables and their interaction can help improve this model useful in application for wildland management regarding wildfire.

BIBLIOGRAPHY

Agee, J.K., 1998. The landscape ecology of western forest fire regimes. *Northwest Science* 72, 24–34.

Agee, J.K., Skinner, C.N., 2005. Basic principles of forest fuel reduction treatments. *Forest Ecology and Management* 211, 83–96.

Alig, R.J., Kline, J.D., Lichtenstein, M., 2004. Urbanization on the US landscape: looking ahead in the 21st century. *Landscape and Urban Planning* 69, 219–234.

Arkle, R.S., Pilliod, D.S., Welty, J.L., 2012. Pattern and process of prescribed fires influence effectiveness at reducing wildfire severity in dry coniferous forests. *Forest Ecology and Management* 276, 174–184.

Bevers, M., Omi, P.N., Hof, J., 2004. Random location of fuel treatments in wildland community interfaces: a percolation approach. *Canadian Journal of Forest Research* 34, 164–173.

Calkin, D.C., Finney, M.A., Ager, A.A., Thompson, M.P., Gebert, K.M., 2011. Progress towards and barriers to implementation of a risk framework for US federal wildland fire policy and decision making. *Forest Policy and Economics* 13, 378–389.

Catchpole, E.A., Hatton, T.J., Catchpole, W.R., 1989. Fire spread through nonhomogeneous fuel modelled as a Markov process. *Ecological Modelling* 48, 101–112.

Cohen, J., 2008. The wildland-urban interface fire problem. *FOREST* 21.

Dombeck, M.P., Williams, J.E., Wood, C.A., 2004. Wildfire policy and public lands: integrating scientific understanding with social concerns across landscapes. *Conservation biology* 18, 883–889.

Duguy, B., Alloza, J.A., Röder, A., Vallejo, R., Pastor, F., 2007. Modelling the effects of landscape fuel treatments on fire growth and behaviour in a Mediterranean landscape (eastern Spain). *International Journal of Wildland Fire* 16, 619–632.

Finney, M.A., 2001. Design of regular landscape fuel treatment patterns for modifying fire growth and behavior. *Forest Science* 47, 219–228.

Finney, M.A., 2006. An overview of FlamMap fire modeling capabilities, in: Andrews, PL, Butler, BW (Comps), *Fuels Management-How to Measure Success: Conference Proceedings*, March. pp. 213–220.

Finney, M.A., 2008. A computational method for optimising fuel treatment locations. *International Journal of Wildland Fire* 16, 702–711.

Fites, J., Campbell, M., Reiner, A., Decker, T., 2007. Fire behavior and effects related to suppression, fuel treatments, and protected areas on the Antelope Complex, Wheeler fire. FireBehaviorAssessmentTeam. Availableonline [www. fs. fed. us/adaptivemanagement/projects/FBAT/docs/Antelope_FINAL3_12_04_07. pdf](http://www.fs.fed.us/adaptivemanagement/projects/FBAT/docs/Antelope_FINAL3_12_04_07.pdf).

Fujioka, F.M., 1985. Estimating wildland fire rate of spread in a spatially nonuniform environment. *Forest Science* 31, 21–29.

Hillier, F., Lieberman, G., 2005. *Introduction to Operations Research*, McGrawHill.

Hof, J., Bevers, M., 1998. Spatial Optimization for Managed Ecosystems, 0 ed. Columbia University Press.

Hof, J., Omi, P.N., Bevers, M., Laven, R.D., 2000. A timing-oriented approach to spatial allocation of fire management effort. *Forest science* 46, 442–451.

Hudak, A.T., Morgan, P., Bobbitt, M.J., Smith, A.M.S., Lewis, S.A., Lentile, L.B., Robichaud, P.R., Clark, J.T., McKinley, R.A., 2007. The relationship of multispectral satellite imagery to immediate fire effects. *Fire Ecology* 3 (1): 64-90. *Fire Ecology Special Issue Vol 3*, 66.

Ireland, K.B., Stan, A.B., Fulé, P.Z., 2012. Bottom-up control of a northern Arizona ponderosa pine forest fire regime in a fragmented landscape. *Landscape ecology* 1–15.

Kalabokidis, K.D., Omi, P.N., 1998. Reduction of fire hazard through thinning/residue disposal in the urban interface. *International Journal of Wildland Fire* 8, 29–35.

Kauffman, J.B., Martin, R.E., 1989. Fire behavior, fuel consumption, and forest-floor changes following prescribed understory fires in Sierra Nevada mixed conifer forests. *Canadian Journal of Forest Research* 19, 455–462.

Kim, Y.H., Bettinger, P., Finney, M., 2009. Spatial optimization of the pattern of fuel management activities and subsequent effects on simulated wildfires. *European Journal of Operational Research* 197, 253–265.

Konoshima, M., Albers, H.J., Montgomery, C.A., Arthur, J.L., 2010. Optimal spatial patterns of fuel management and timber harvest with fire risk. *Canadian Journal of Forest Research* 40, 95–108.

Loehle, C., 2004. Applying landscape principles to fire hazard reduction. *Forest Ecology and Management* 198, 261–267.

Martell, D.L., Network, S.F.M., 2004. A FireSmart approach to integrated fire and forest management in the boreal forest region of Canada. Sustainable Forest Management Network.

Massada, A.B., Radeloff, V.C., Stewart, S.I., 2011. Allocating fuel breaks to optimally protect structures in the wildland–urban interface. *International Journal of Wildland Fire* 20, 59–68.

Mell, W.E., Manzello, S.L., Maranghides, A., Butry, D., Rehm, R.G., 2010. The wildland–urban interface fire problem–current approaches and research needs. *International Journal of Wildland Fire* 19, 238–251.

Moghaddas, J.J., Craggs, L., 2008. A fuel treatment reduces fire severity and increases suppression efficiency in a mixed conifer forest. *International Journal of Wildland Fire* 16, 673–678.

Murphy, K., Rich, T., Sexton, T., 2007. An assessment of fuel treatment effects on fire behavior, suppression effectiveness, and structure ignition on the Angora Fire. USDA Forest Service, Pacific Southwest Region. Gen. Tech. Rep. R 5, 1–38.

Price, O.F., 2012. The Drivers of Effectiveness of Prescribed Fire Treatment. *Forest Science* 58, 606–617.

Pyne, S.J., Andrews, P.L., Laven, R.D., 1996. Introduction to wildland fire. John Wiley & Sons Inc.

Radeloff, V.C., Hammer, R.B., Stewart, S.I., Fried, J.S., Holcomb, S.S., McKeefry, J.F., 2005. The wildland-urban interface in the United States. *Ecological applications* 15, 799–805.

Region, P.N., 2007. An Assessment of Fuel Treatments on Three Large 2007 Pacific Northwest Fires.

Reinhardt, E.D., Keane, R.E., Calkin, D.E., Cohen, J.D., 2008. Objectives and considerations for wildland fuel treatment in forested ecosystems of the interior western United States. *Forest Ecology and Management* 256, 1997–2006.

Rideout, D.B., Ziesler, P.S., Kling, R., Loomis, J.B., Botti, S.J., 2008. Estimating rates of substitution for protecting values at risk for initial attack planning and budgeting. *Forest Policy and Economics* 10, 205–219.

Rodriguez Gonzalez, J., del Barrio, G., Duguy, B., 2008. Assessing functional landscape connectivity for disturbance propagation on regional scales—A cost-surface model approach applied to surface fire spread. *ecological modelling* 211, 121–141.

Schoennagel, T., Nelson, C.R., Theobald, D.M., Carnwath, G.C., Chapman, T.B., 2009. Implementation of National Fire Plan treatments near the wildland–urban interface in the western United States. *Proceedings of the National Academy of Sciences* 106, 10706.

Spyratos, V., Bourgeron, P.S., Ghil, M., 2007. Development at the wildland–urban interface and the mitigation of forest-fire risk. *Proceedings of the National Academy of Sciences* 104, 14272.

Thompson III, F.R., Probst, J.R., Raphael, M.G., 1995. Impacts of silviculture: overview and management recommendations. Ecology and management of Neotropical migratory birds. Oxford University Press, Oxford, United Kingdom 201–219.

Toman, E., Stidham, M., Shindler, B., McCaffrey, S., 2011. Reducing fuels in the wildland–urban interface: community perceptions of agency fuels treatments. International Journal of Wildland Fire 20, 340–349.

Van Wagtendonk, J.W., 1995. Large fires in wilderness areas, in: Proceedings: Symposium on Fire in Wilderness and Park Management. pp. 113–116.

Viedma, O., Angeler, D.G., Moreno, J.M., 2009. Landscape structural features control fire size in a Mediterranean forested area of central Spain. Int. J. Wildland Fire 18, 575–583.

Weatherspoon, C.P., Skinner, C.N., 1996. Landscape-level strategies for forest fuel management, in: Sierra Nevada Ecosystem Project: Final Report to Congress. pp. 1471–1492.

Wei, Y., 2012. Optimize landscape fuel treatment locations to create control opportunities for future fires. Canadian Journal of Forest Research 42, 1002–1014.

Wei, Y., Rideout, D., Kirsch, A., 2008. An optimization model for locating fuel treatments across a landscape to reduce expected fire losses. Canadian Journal of Forest Research 38, 868–877.

Wolsey, L.A., 2000. Integer programming. IIE Transactions 32, 273–285.

APPENDICES

Table 4. The stand's probability of ignition used in Scenarios A, C, D, E; and the rearranged ignition probability used in Scenario B.

Stand ID	Probability of ignition In Scenarios A, C, D, E	Rearranged probability Used in Scenario B
0	0.000	0
1	0.012	0.007
2	0.022	0.015
3	0.013	0.013
4	0.009	0.007
5	0.010	0.011
6	0.006	0.013
7	0.021	0.015
8	0.007	0.009
9	0.011	0.012
10	0.005	0.010
11	0.018	0.010
12	0.007	0.009
13	0.016	0.013
14	0.007	0.013
15	0.018	0.013
16	0.013	0.007
17	0.015	0.005
18	0.009	0.016
19	0.013	0.019
20	0.007	0.006
21	0.019	0.018
22	0.012	0.005
23	0.010	0.011
24	0.011	0.021
25	0.013	0.007
26	0.015	0.006
27	0.007	0.018
28	0.005	0.012
29	0.013	0.007
30	0.006	0.022